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A Structural Equation Modeling Analysis on Solvency, Operation and Profitability of Life Insurers

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Abstract: The abilities of life insurers can be divided and measured from various aspects. Through the use of structural equation modeling, we investigate the relations among solvency, operation ability and profitability in year 1994, 1995 and 1996. After within-year analysis and longitudinal data analysis, we found that operation ability has a positive influence on the size and income of life insurers and has a slight negative effect on the return on capital during these years. While the effect of solvency, asset risk and product risk on return on capital is not significant.

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Introduction

This paper focuses on three important indicators of life insurers. Pursuing high profitability is a vital goal for a company – life insurers are no exception. Solvency and growth potential are two other important indicators, and the three interact with each other. In fact, the relationships between these three are complicated and life insurers have to find a way to boost profitability, solvency and growth potential. Plenty of papers have done significant amount of research on how these three are represented by more detailed indicators on balance sheet, and how these three correlate with each other, or any two of them, or any of these indicators correlate with other indicators. For example, in Conant, Desouter, Long and MacGrogan's book <Managing for Solvency and Profitability in Life and Health Insurance Companies>, the authors discussed solvency and profitability from the perspective of management. Dragana Ikonic and Nina Arsic[1] analyzed growth potential and profitability of insurance companies in Serbia. Another example is Milton Nektarios' work. He discussed the growth theory of insurance companies from the view of economy[2], to name just a few. Plus, many methods are devised to measure the performance of life insurers and other companies. For example, some use cluster analysis to analyze financial indicators of certain type of companies. In Yan and Kung, 2010, (<Business Performance Assessment of Insurance Company via Grey Rational Analysis>), they use grey rational analysis to measure the financial performance of insurance companies in Taiwan. Grey Rational Analysis uses a specific concept of information. It defines situations with no information as black, and those with perfect information as white. However, neither of these idealized situations ever occurs in real world problems. Since uncertainty always exists, one is always somewhere in the middle,

1 Ikonić, and Arsić (2011).
2 Nektarios (2010).

somewhere between the extremes, somewhere in the grey area[3]. In their paper, they used some special formula to calculate grey rational grade, then rank the sequence according to the value. In this way, they ranked the performance of the companies. And some other papers just use basic linear regression.

Confirmatory Factor Analysis with Structural Equation Modeling (SEM) is an ideal way to deal with these kinds of intertwining-variable problems, and that is what we plan to use in this paper. Structural equation modeling (SEM) is a statistical technique for testing and estimating causal relations using a combination of statistical data and qualitative causal assumptions[4]. It is a relatively young field compared with other statistical methods such as regression. In SEM, interest usually focuses on latent constructs – abstract variables, or in other words, abstract concepts such as “intelligence”, “attitude” or “competence” – rather than on the manifest variables used to measure these constructs. Measurement is recognized as difficult and error-prone. By explicitly modeling measurement error, SEM users seek to derive unbiased estimates for the relations between latent constructs[5]. SEM has been widely used in social science and psychology areas, because of its great advantage in dealing with complicated relations among various variables. Due to its characteristics described above, SEM can also be introduced to cases in financial areas, such as the scenario in this paper. We would like to do research on three important but abstract indicators, see how these correlate with each other. These three abstract indicators can be attributed to more concrete indicators, which can be quantified and found on balance sheet. For example, the solvency of an insurance company can be reflected on concrete financial indicators such as return on assets and

3 http://en.wikipedia.org/wiki/Grey_relational_analysis
4 Source: Wikipedia, http://en.wikipedia.org/wiki/Structural_equation_modeling
5 Source: http://www2.gsu.edu/~mkteer/sem.html

premium per capita. All of these characteristics indicate that SEM is a good choice for analyzing this situation.

We choose confirmatory factor analysis (CFA) rather than exploratory factor analysis (EFA) to deal with this case. Confirmatory factor analysis is used to test whether measures of a construct are consistent with a researcher's understanding of the nature of that construct (or factor)[6]. So a researcher should have a solid theoretical understanding of the data of the related field in advance, then make one or more hypothetical models. Then we use confirmatory factor analysis to test whether the data fit the hypothesized measurement model. In this paper, we will first make a solid review of the related work done by other researchers, that is, why and how these three abstract indicators can be related to the concrete indicators on balance sheet, how these three correlate with each other themselves. Based on these, we then make assumptions and build hypothetical models. Afterwards, we use empirical data to see how fit the model is.

Since the object of our research is life insurers, we need to clarify the following in advance: on analyzing performances, what justifies focus upon life insurers as a sector apart from industrial firms? The definition of insurance is "Insurance is the equitable transfer of the risk of a loss, from one entity to another in exchange for payment. It is a form of risk management primarily used to hedge against the risk of a contingent, uncertain loss"[7]. The central part of insurance service is "risk", which can cause huge difference when dealing with capital structures. In insurance companies, due to their special characteristics, it is vital for them to manage the interrelationships between capital and risks. Compared with nonfinancial companies, they are more subject to regulations, because the failure of insurers to meet their obligations to pay claims would harm a large

6 Source: http://en.wikipedia.org/wiki/Confirmatory_factor_analysis
7 Source: http://en.wikipedia.org/wiki/Insurance

number of people and impose a substantial cost upon society. These laws constrain insurer discretion in managing the interrelationship between capital and risks. The intention is to guarantee that life and health insurers have adequate capital, per regulatory formulae, to buffer their investment risks and protect their solvency. Thus, life and health insurers are not free to pursue unbounded value maximization[8].

8 Baranoff and Sager, 2012

RELATED WORK

As mentioned above, related work on similar subject or similar methodology has been done:

Research on similar subject using different methods other than SEM

The performance of insurance companies is a long-lasting topic researched by different scholars from different countries. Various methods have been devised on measuring the performance of insurance companies. In <Determinants of Performance: A Case of Life Insurance Sector of Pakistan>, N. Ahmed, Z. Ahmed and A. Usman used OLS regression, and chose seven independent variables (leverage, tangibility, size, etc.) to predict dependent variable "life insurers' performance". They conclude that size, risk and leverage are important determinants of performance of life insurance companies of Pakistan. One limitation of this work is that the authors directly used "Net income before interest and tax divided by total assets" to measure performance, which can be a bit limited, for the performance of one company should be represented in various aspects rather than one. In the paper <Determinants of Profitability of Indian Life Insurers – An Empirical Study>, Charumathi used similar regression analysis to discuss the profitability determinants in Indian life insurers. This paper used Return on Assets as the indicator for profitability. The author discovered that the profitability of the Indian life insurers is significantly and positively related with size and liquidity, and negatively related with leverage, premium growth and equity capital. One limitation for the work is the small sample. Although the author took all the life insurers in India into consideration, the sample size is only 23 (1 public, 22 private). The small sample size might be a disadvantage.

Other methods have been used to analyze the performance related indicators of life insurers and similar financial organizations. In <Business Performance Assessment of Insurance Company via Grey Relational Analysis>, Yan & Kung provides an alternative to evaluate and rank the performances of 15 insurance companies in Taiwan. This method improves the issue of small sample size, for it is non-parametric method and does not require the sample to be normally distributed. 24 factors (return on assets, return of investments, debt ratio, asset turnover, etc.) are chosen, and were divided into 5 categories: capital structure, profitability, debt servicing capability and business efficiency and capital employment. This method provides an efficient and fairly unbiased way to measure and rank the performance of insurance companies while taking overall factors into consideration. Nevertheless, it does not focus on the analysis of the interactions and relationships within latent factors. It emphasizes more on individual measurement.

Research on different subjects but using the methodology of SEM

As mentioned above, SEM is a statistical method that can be used in different fields, such as psychology, education, finance and other areas, as long as data type and research topic fit the SEM model. In <Intellectual Capital Management Enablers: A Structural Equation Modeling Analysis> (Isaac, Herremans, Kline), they used SEM to analyze the intellectual capital of companies, several latent factors were used: organic renewal structure, interactive behavior, trust, human capital, organizational capital and relationship capital. Based on theoretical backgrounds, they developed some hypotheses, which is the vital part in building SEM structure for this case. They hypothesized that an organic renewal environment leads to interactive behavior, thus building trust, and finally enabling intellectual capital systems[9]. Along with other hypotheses, they applied survey data to their model, these data were regarded as measurements of these latent factors, and because they are categorical (scale of 5), factor analysis of categorical data is applied. The conclusion was that the best statistical fit being an organic renewal environment providing a foundation for interactive behaviors, which led to trust, thus consistent with the development of intellectual capital management processes within the organization[10].

Another impressive and representative example using SEM would be <Capital and Risk Revisited: a Structural Equation Model Approach for Life Insurers> (Baranoff, Papadopoulous, Sager). Different from the example above, they use longitudinal factor analysis to examine the relationship between capital and risk in life insurers. First of all, the authors categorized the risk into two kinds: asset risk and product risk based on their origins: investing and underwriting respectively. Then they focused on asset risk: there are two kinds of measurement proxies on asset risk: regulatory asset risk (RAR) and opportunity asset risk (OAR). These are neither same nor completely different, they can be regarded as somewhat overlapping. This characteristic is very fit for SEM. They would like to compare the holistic roles in capital structure under similar conditions[11]. To build such condition, they devised a longitudinal data based structural equation model. Observable variables are capital ratio, RAR ("penalty-weighted average" of various assets in insurer's portfolio), OAR (an approximation of volatility of actual returns), health product risk (highest risk), annuity product risk (lowest risk) with control variables (size, group membership and organizational type). They then devised three latent fators:

9 Robert G. Issac, Irene M. Herremans, Theresa J. Kline, <Intellectual Capital Management Enablers: A Structural Equation Modeling Analysis>, Journal of Business Ethics (2010) 93:373–391, page 378

10 Robert G. Issac, Irene M. Herremans, Theresa J. Kline, <Intellectual Capital Management Enablers: A Structural Equation Modeling Analysis>, Journal of Business Ethics (2010) 93:373–391, page 373

11 Etti G. Baranoff, Savas Papadopoulous, Thomas W. Sager, <Capital and Risk Revisited: A Structural Equation Model Approach for Life Insurers>, The Journal of Risk and Insurance, 2007, Vol. 74, No.3, 653 – 681, page 668

asset risk factor, health product risk factor and annuity risk factor. Each is to explain the corresponding observable variables and capital ratio, each is determined by their own factor in the last period, and is correlated with each other. They divided their sample into two parts according to the size of insurers: large and small, and three parts according to the time periods. For each group, they ran the model twice: under RAR and under OAR, ceteris paribus. The correlation coefficient results revealed important information on the comparison between RAR and OAR, between small and large insurers and between different time periods.

Apart from those, SEM can lead to a variety of other methods, such as Behavioral Genetic Models, Growth Curve Analysis, Latent Different Score Analysis and nonlinear factor analysis are all important methods under the framework of SEM.

In this paper, we built several Structural equation models, in order to discover the relation between different competences of life insurers, both within each year and longitudinally. After the analysis, we found that operation ability has a slight negative effect on the return on capital during these years. While the effect of solvency, asset risk and product risk on return on capital is not significant and unclear. The following part will present a detailed illustration of the models and the results.

OBSERVABLE VARIABLES

In this report, we use data from NAIC about life insurers all over United States from 1994 to 1996. We use this period because there are some financial instability during the 21st century, the 2008 financial crisis is an example. The external economic environment can exert considerable impact on life insurers, while year 1994, 1995 and 1996 are relatively stable. Furthermore, the relevant regulation laws also did not change much during that period, thus provided a consistent regulation environment. There are 2244 companies in the sample, multiplied by 3 years, so the total individual number is 2244 * 3 = 6732. However, there are some data missing, so there are smaller sample size when doing the SEM, since we used pairwise deletion. But since most data are intact, we still have enough sample size. The following is the description of the observable variables we use in this report.

logAtotal

This is the logarithm of total assets of life insurers and is a basic measure of company size. Since the size of each life insurers varies considerably, the distribution of the original total assets data is skewed. Taking logarithm solved this issue. We initially believe that the total assets of a certain company has something to do with its operation ability. We will discuss issue more in the "hypothesis" part. The following form is a simple statistical summary of the observable variable "logAtotal".

	N	**Mean**	**Std. Dev**	**Min**	**Max**
1994	1796	17.865	2.980	10.891	25.881
1995	1749	17.952	3.016	10.028	25.952
1996	1626	18.022	3.007	9.953	25.952

Table 1: Log (Total Assets) Summary

Logincome

This is the logarithm of annual income of each life insurer. The reason for taking the logarithm of the annual income is the same as that of "Total Assets" above, to correct the skewed distribution. Since we took the log, we only analyze companies who produce positive income. Furthermore, we found that those have negative income can form a separate normal distribution of their own, if we take out their negative signs and take then take logarithm. So we only focus on those who generated positive annual income. This can also reflect the size of a company to some extent, and how well a company is operating in a certain year. Consequently, this observable variable will be connected to "operation ability", which will be discussed in detail in the next part. The following form is a simple statistical summary of the observable variable "logIncome".

	N	**Mean**	**Std.Dev**	**Min**	**Max**
1994	1487	14.133	2.513	2.485	20.107
1995	1443	14.264	2.596	5.273	20.438
1996	1349	14.349	2.683	4.745	20.731

Table 2: log (annual income) summary

ROC (Return on Capital)

We use "ROC" to represent "return on capital". In accounting, return on capital is defined as net operating profit less adjusted taxes divided by invested capital[12]. It is one of the most common measures to estimate a certain company's ability to profit. In this report, we use this observable variable to measure "profitability" of life insurers.

12 Source: https://en.wikipedia.org/wiki/Return_on_capital

However, since “profitability” is closely linked with other abilities of a certain company, variable “ROC” will correlate with other latent factors as well. This will be illustrated further in the following model description part. The following form is a simple statistical summary of the observable variable “ROC”.

	N	Mean	Std.Dev	Min	Max
1994	1463	0.082	0.259	-2.349	4.928
1995	1443	0.112	0.746	-5.257	17.544
1996	1373	0.067	0.323	-6.55	2.727

Table 3: Return on Capital Summary

OAR (Opportunity Asset Risk)

The observable variable “OAR” stands for “opportunity asset risk”, this is an index calculated initially by Baranoff, Papadopoulous and Sager in <Capital and Risk Revisited: A Structural Equation Model Approach for Life Insurers>[13]. One major activity of life insurers is investing, and the risks associated with that activity is called asset risk. One measure of it is called opportunity asset risk, based on traditional finance concerns with market risk and reflects volatility of returns[14]. The calculation process is very complicated, in short, they calculated an proxy for life insurers' monthly earnings first, and then used these results to get the normalized standard deviation of a whole year to measure the volatility[15]. The “OAR” we use here is the logarithm of the normalized standard deviation. Since the level of asset risk of a certain life insurer is closely linked

13 Baranoff, Papadopoulous and Sager (2007).
14 Baranoff, Papadopoulous and Sager (2007).
15 See Baranoff, Papadopoulous and Sager (2007), <Capital and Risk Revisited: A Structural Equation Model Approach for Life Insurers>, <The Journal of Risk and Insurance, 2007, Vol.74, No. 3>, Page 661 for calculation detail.

with its solvency ability, so we connect this “OAR” variable with latent factor “solvency”, which will be discussed later. The following form is a simple statistical summary of the observable variable “OAR”.

	N	Mean	Std.Dev	Min	Max
1994	1864	-5.139	0.454	-12.260	-4.100
1995	1812	-5.481	0.490	-10.920	-4.535
1996	1645	-5.870	0.641	-12.052	-3.665

Table 4: Opportunity Asset Risk Summary

RAR (Regulatory Asset Risk)

The observable variable “RAR” stands for “regulatory asset risk”, this is also an index calculated initially by Baranoff, Papadopoulous and Sager in <Capital and Risk Revisited: A Structural Equation Model Approach for Life Insurers>[16]. As mentioned above, one way to measure asset risk is based on traditional financial concerns, while this “RAR” variable is based on another perspective. Regulatory asset risk derives from the regulatory tradition of concern with solvency and is related to the C-1 component of risk-based capital[17]. The calculation process is also complicated. In short, it is a weighted average index. To be more specific, it calculated raw regulatory asset risk measure based on C-1 component of risk-based capital. They adopted bond quality classes 1-6, common stocks, preferred stocks, total mortgages, real estate, short-term investments and cash, put “penalty weights” on each one of them (that is to say, the riskier the item is, the more weight it will get), then added them together to calculate the weighted average of them.

16 Baranoff, Papadopoulous and Sager (2007).

17 Baranoff, Papadopoulous and Sager (2007).

Then the index got normalized and finally we take the logarithm[18]. Similar to opportunity asset risk, regulatory asset risk is also closely linked with the solvency of life insurers, for it is just another measure of asset risk from a different perspective. The following form is a simple statistical summary of the observable variable “RAR”.

	N	**Mean**	**Std.Dev**	**Min**	**Max**
1994	1796	-4.519	1.277	-10.706	-1.208
1995	1748	-4.535	1.289	-11.049	-1.209
1996	1557	-4.438	1.254	-11.356	-1.208

Table 5: Regulatory Asset Risk Summary

HP (Health Insurance Product Proportion)

In this report, “HP” stands for “Health Insurance Product Proportion”. Life insurers usually issue several insurance products, such as health insurance products, annuity insurance products, reinsurance products and life products. This “HP” means firm premiums of health insurance products divided by the total premium. We include “HP” along with “AP” (introduced in the following, standing for “Annuity Insurance Product Proportion” mainly for product risk concerns. Product risk is a critical matter when analyzing life insurers, for the risks of different products vary considerably. Previous researchers[19] have shown that health insurance product has the highest risk among all of the products, for it is not much likely to predict when one will get sick, plus it is also probable for someone to not be able to pay back his or her bills. Undoubtedly

18 See Baranoff, Papadopoulous and Sager (2007), <Capital and Risk Revisited: A Structural Equation Model Approach for Life Insurers>, <The Journal of Risk and Insurance, 2007, Vol.74, No. 3>, Page 661 for calculation detail.
19 Baranoff and Sager (2002 and 2003).

the insurers with more health insurance services are subject to higher risks, so we use health insurance product proportion as one observable variable. This observable variable "HP" will be connected with the latent variable "product risk", which will also be mentioned later. Since "HP" is a proportion, we multiplied it by 100 to make it easier to read. The following form is a simple statistical summary of the observable variable "HP".

	N	Mean	Std.Dev	Min	Max
1994	1796	24.571	38.977	-742.334	117.529
1995	1749	22.827	115.180	-4564	109.121
1996	1627	26.186	35.894	-31.603	132.261

Table 6: Health Product Proportion Summary

AP (Annuity Insurance Product Proportion)

As mentioned above, "AP" stands for annuity insurance product proportion, and is calculated in the same manner as that in "HP". We specifically only chose these two because these two are most representative, for "AP" represents the products with lowest risk and "HP" represents those with highest risk. Annuity insurance product is least risky is mainly due to its traits. An annuity product issued by life insurers is a financial contract in the form of an insurance product according to which an insurer makes a series of future payments to an annuitant in exchange for the immediate payment of a single-payment annuity or a series of regular payments, prior to the onset of the annuity[20]. As we can see from the definition of annuity, it is much more determined than that of health insurance products, thus much less risky. The risks of other products are between these two and are

20 Source: http://en.wikipedia.org/wiki/Life_annuity

not as representative, so we omitted them for model parsimony reasons. The following form is a simple statistical summary of the observable variable “AP”.

Annuity Product Proportion Summary

	N	**Mean**	**Std.Dev**	**Min**	**Max**
1994	1796	16.490	30.849	-24.879	505.263
1995	1749	16.046	28.395	-2.072	108.478
1996	1627	15.703	28.512	-3.399	100

Table 7: Annuity Product Proportion Summary

In order to summarize, the following is the three correlation tables of these observable variables in year 1994, 1995 and 1996 respectively.

Pearson Correlation Coefficients Prob > |r| under H0: Rho=0 Number of Observations							
	oar	**rar**	**LogATotal**	**LogIncome**	**hp**	**ap**	**roc**
oar	1.00000 1864	0.25660 <.0001 1796	-0.13597 <.0001 1796	-0.11225 <.0001 1487	0.04065 0.0850 1796	-0.06135 0.0093 1796	-0.03063 0.2417 1463
rar	0.25660 <.0001 1796	1.00000 1796	0.37084 <.0001 1796	0.37835 <.0001 1487	0.08781 0.0002 1796	0.04297 0.0687 1796	-0.01416 0.5883 1463
LogATotal log(Total assets)	-0.13597 <.0001 1796	0.37084 <.0001 1796	1.00000 1796	0.87991 <.0001 1487	0.00134 0.9546 1796	0.46360 <.0001 1796	-0.02702 0.3017 1463
LogIncome log(Income)	-0.11225 <.0001 1487	0.37835 <.0001 1487	0.87991 <.0001 1487	1.00000 1487	0.08126 0.0017 1487	0.33024 <.0001 1487	0.13540 <.0001 1222
hp	0.04065 0.0850 1796	0.08781 0.0002 1796	0.00134 0.9546 1796	0.08126 0.0017 1487	1.00000 1796	-0.42109 <.0001 1796	0.04770 0.0681 1463
ap	-0.06135 0.0093 1796	0.04297 0.0687 1796	0.46360 <.0001 1796	0.33024 <.0001 1487	-0.42109 <.0001 1796	1.00000 1796	-0.08693 0.0009 1463
roc	-0.03063 0.2417 1463	-0.01416 0.5883 1463	-0.02702 0.3017 1463	0.13540 <.0001 1222	0.04770 0.0681 1463	-0.08693 0.0009 1463	1.00000 1463

Table 8: Year 1994 observable variables correlation

Pearson Correlation Coefficients Prob > |r| under H0: Rho=0 Number of Observations							
	oar	**rar**	**LogATotal**	**LogIncome**	**hp**	**ap**	**roc**
oar	1.00000 1812	0.46645 <.0001 1748	0.26575 <.0001 1749	0.25990 <.0001 1443	0.03199 0.1811 1749	0.11416 <.0001 1749	0.00113 0.9657 1443
rar	0.46645 <.0001 1748	1.00000 1748	0.38510 <.0001 1748	0.42755 <.0001 1443	0.04630 0.0529 1748	0.06602 0.0058 1748	-0.04870 0.0645 1442
LogATotal log(Total assets)	0.26575 <.0001 1749	0.38510 <.0001 1748	1.00000 1749	0.89087 <.0001 1443	0.02322 0.3317 1749	0.49344 <.0001 1749	-0.08352 0.0015 1443
LogIncome log(Income)	0.25990 <.0001 1443	0.42755 <.0001 1443	0.89087 <.0001 1443	1.00000 1443	0.04418 0.0934 1443	0.37410 <.0001 1443	0.05332 0.0647 1201
hp	0.03199 0.1811 1749	0.04630 0.0529 1748	0.02322 0.3317 1749	0.04418 0.0934 1443	1.00000 1749	-0.07923 0.0009 1749	-0.01135 0.6666 1443
ap	0.11416 <.0001 1749	0.06602 0.0058 1748	0.49344 <.0001 1749	0.37410 <.0001 1443	-0.07923 0.0009 1749	1.00000 1749	0.01037 0.6939 1443
roc	0.00113 0.9657 1443	-0.04870 0.0645 1442	-0.08352 0.0015 1443	0.05332 0.0647 1201	-0.01135 0.6666 1443	0.01037 0.6939 1443	1.00000 1443

Table 9: Year 1995 observable variables correlation

Pearson Correlation Coefficients Prob > |r| under H0: Rho=0 Number of Observations							
	oar	**rar**	**LogATotal**	**LogIncome**	**hp**	**ap**	**roc**
oar	1.00000 1645	0.67329 <.0001 1557	0.12607 <.0001 1557	0.15152 <.0001 1286	0.02644 0.2971 1557	-0.01216 0.6315 1557	0.00943 0.7334 1307
rar	0.67329 <.0001 1557	1.00000 1557	0.31185 <.0001 1557	0.33907 <.0001 1286	0.02808 0.2682 1557	0.04222 0.0959 1557	-0.03892 0.1596 1307
LogATotal log(Total assets)	0.12607 <.0001 1557	0.31185 <.0001 1557	1.00000 1626	0.89030 <.0001 1348	-0.02325 0.3488 1626	0.49004 <.0001 1626	0.05385 0.0460 1373
LogIncome log(Income)	0.15152 <.0001 1286	0.33907 <.0001 1286	0.89030 <.0001 1348	1.00000 1349	0.05023 0.0651 1349	0.37302 <.0001 1349	0.22369 <.0001 1148
hp	0.02644 0.2971 1557	0.02808 0.2682 1557	-0.02325 0.3488 1626	0.05023 0.0651 1349	1.00000 1627	-0.31065 <.0001 1627	-0.13653 <.0001 1373
ap	-0.01216 0.6315 1557	0.04222 0.0959 1557	0.49004 <.0001 1626	0.37302 <.0001 1349	-0.31065 <.0001 1627	1.00000 1627	-0.00791 0.7697 1373
roc	0.00943 0.7334 1307	-0.03892 0.1596 1307	0.05385 0.0460 1373	0.22369 <.0001 1148	-0.13653 <.0001 1373	-0.00791 0.7697 1373	1.00000 1373

Table 10: Year 1996 observable variables correlation

Latent Factors

Since we would like to measure the different "competence" or "ability" of life insurers, and these concepts are usually too abstract to be measured by one single observable variable, we set them as latent factors consequently. As mentioned in the introduction part, we would like to see how life insurers' solvency ability, operation ability and profitability correlate with each other, taking product risk into consideration. Since we consider "ROC" (return on capital) as a direct measure for profitability, we actually have the following latent factors： product risk, asset risk, solvency and operation.

Hypotheses

Before doing the analysis, we made the following prior assumptions:

1. Operation ability can determine the size and income of one certain life insurer to some extent. Size may be considered an operational factor, since the insurer's business is conducted in an environment that may be affected by the scope of operations[21]. Here we use logarithm of total assets and neglog of annual income to represent that.
2. Regulatory asset risk, opportunity asset risk, health product risk and annuity product risk can represent most of the risks in life insurers, and the risks of life insurers can determine the solvency ability of a certain insurer to some extent. The higher the risk is, the poorer solvency ability it will get.

We then made the following hypotheses in order to test them in the data analysis:

1. Profitability (represented by Return on Assets) can be affected by every latent factor. That is to say, in our models, every latent factor can influence "roc". For example, we suppose asset risk, product risk, operation ability and solvency ability can all have some impact on profitability. However, there is not a standard conclusion on how these factors will influence profitability. So we will use these models to check if there is an influence, and if there is, check if it is a positive or negative one.
2. Operation ability is associated with product risk, asset risk and solvency ability. In our models, we will see them correlate with operation ability respectively.

21 Baranoff, Sager and Shi (2012).

3. Operation ability has a positive influence on the size and income of life insurers. That is to say, we suppose to see a significant and positive loading from "operation" factor on observable variable "logAtotal" and "logIncome".
4. The operation of the life insurers runs smoothly during these three years.

MODELS DESCRIPTION

As mentioned above, we use structural equation modeling to fit and analyze the data in this report. Structural equation modeling is most widely used in psychology and social science survey data analysis. The reasons we use SEM rather than OLS regression or other methods are the following: simple linear regression cannot analyze the relation between different endogenous variables at the same time. Secondly, we would like to do research on some abstract concepts rather than concrete measurements in this report, a structural equation model can have latent factors to meet that request, while this is not possible in linear regression. Furthermore, we can even see how latent factors interact with each other with the use of SEM. Above all, SEM is an ideal choice for this scenario.

The basic structure we need for structural equation models is path diagrams, which are based on the theoretical view of the specific field, in this case, insurance industry and the related theories. The previous "hypotheses" part suggests that the path diagrams for this report could have potentially many different forms. We will draw several path diagrams for the analysis, since we would like to see if different "competences" or "abilities" are connected with each other, both within the same year and longitudinally. Keeping the model parsimonious is a prerequisite. The following part will illustrate the path diagrams we will use one by one. Model one, two and three analyzes data within same year, model four, five and six analyzes data longitudinally.

Path diagram of Model 1:

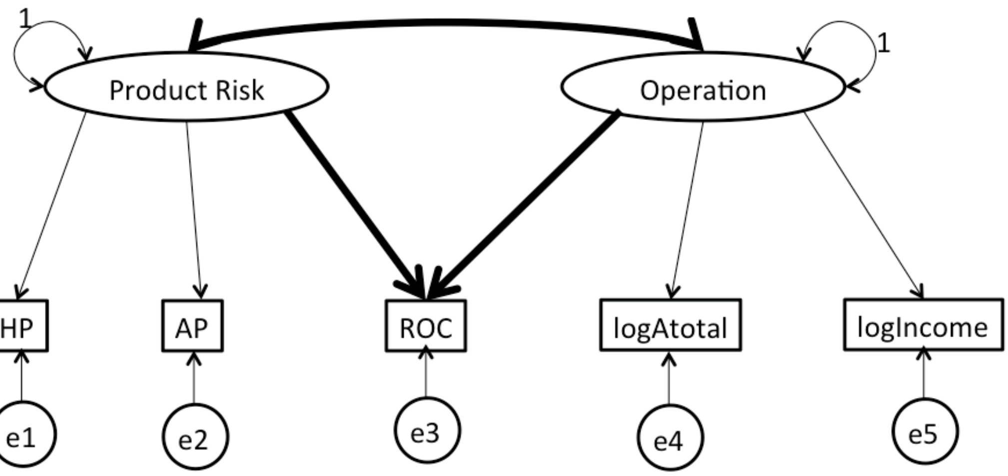

Figure 1: Model1 Path Diagram

With this path diagram, we would like to analyze the relationship between life insurers' operation ability and profitability, taking product risk into consideration. "HP" means health insurance product proportion (multiplied by 100), "AP" means annuity product proportion (multiplied by 100), "ROC" means return on asset, "logAtotal" means logarithm of total assets, "logincome" means log transformation of annual income. Since we use return on capital as indicator for profitability, so here we would specifically like to concern the following coefficients: the arrow from "product risk" to "roc", the arrow from "operation" to "roc" and the bi-arrow between "product risk" and "operation". We will run the model three times, with data from 1994, 1995 and 1996 respectively.

Path diagram of Model 2:

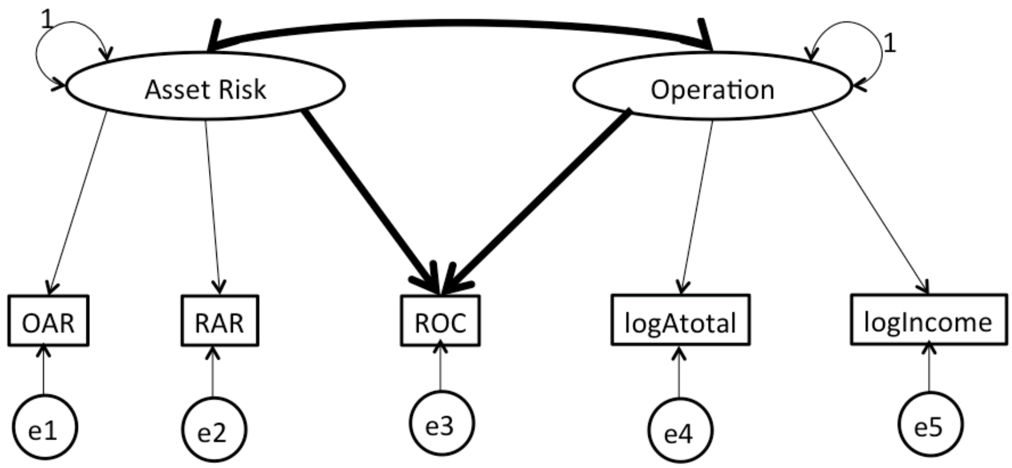

Figure 2: Model2 Path Diagram

With this path diagram, we would still like to analyze the relationship between life insurers' operation ability and profitability, while taking asset risk into consideration this time. "OAR" means logarithm of opportunity asset risk, "RAR" means logarithm of regulatory asset risk, "ROC" means return on asset, "logAtotal" means logarithm of total assets, "log" means logarithm of annual income. We would still use return on capital as the measurements for profitability. Here we pay attention to these coefficients: the arrow from "asset risk" to "ROC", the arrow from "operation" to "ROC", and the bi-arrow between "asset risk" and "operation". We will still run the model three times, with data from 1994, 1995 and 1996 respectively. In short, compared with Model 1, this is just switching from product risk to asset risk, ceteris paribus.

Path diagram of Model 3:

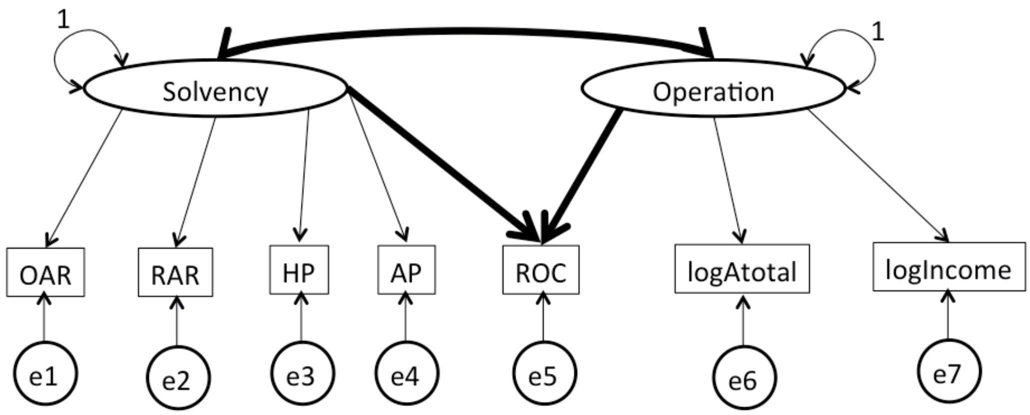

Figure 3: Model3 Path Diagram

The third model is to some extent the combination of Model 1 and Model 2, however, this is not exactly the case. The effect of combining asset risk measures and product risk measures into one latent factor is not additive. As mentioned in the hypotheses part previously, the solvency ability of a life insurer is closely linked with its risks, so these four risk-related observable variables (oar, rar, hp and ap) have represented the holistic risks of a certain life insurer mostly and to some extent represented one insurance company's solvency ability. In this model, we will discover how close these links are. The variables we use here are the same ones we used in the previous two models, so it does not need to be illustrated again. Now we would like to put emphasis on the following coefficients: the arrow from "solvency" to "ROC", the arrow from "operation" to "ROC" and the bi-arrow between "solvency" and "operation". We need to look at other coefficients as well, but these three can tell the relation between solvency, return on capital and operation. Still, we run the model three times, with data from 1994, 1995 and 1996.

Path diagram of Model 4:

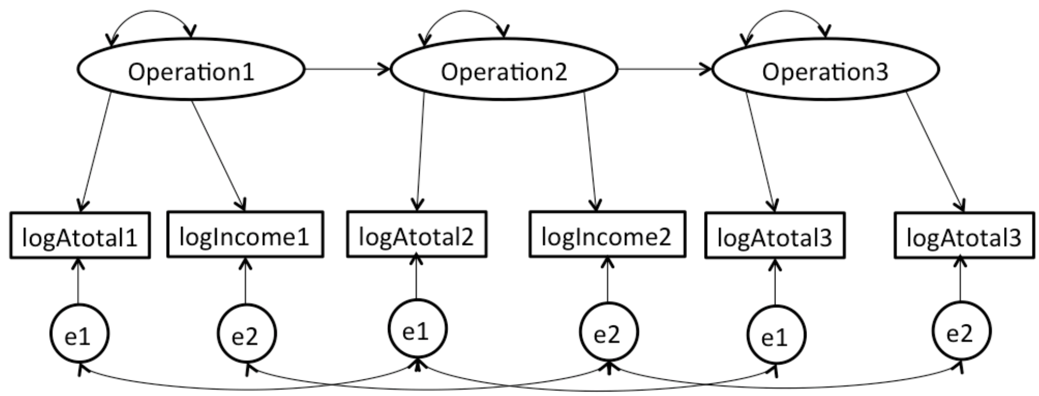

Figure 4: Model4 Path Diagram

Unlike the previous three models, in this model, we analyze one single latent factor from a longitudinal perspective. "LogAtotal1" means logarithm of total assets in 1994, "logAtotal2" means logarithm of total assets in 1995, and "logAtotal3" in 1996. The three "logincome" can be explained in the same manner. In this model, we would like to see if the operation ability of previous year will have some influence on that of next year, and how big it is if there is any. We will also see the gradual changes of relation between latent factors and observable variables.

Path diagrams of Model 5:

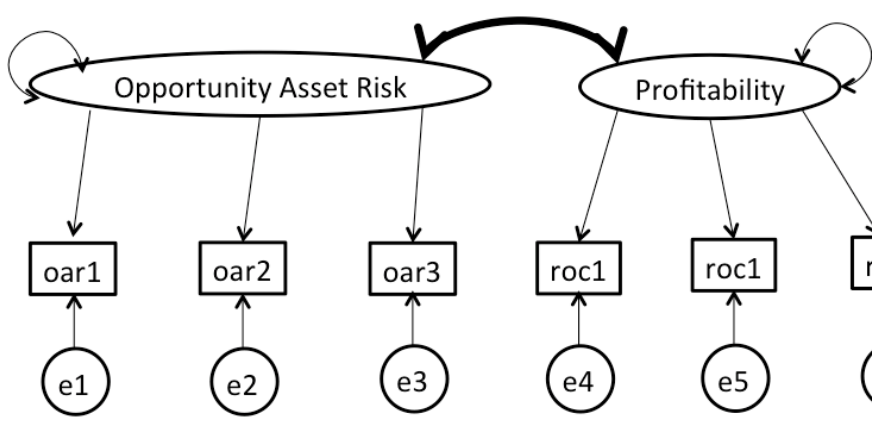

Figure 5: Model5 Path Diagram1

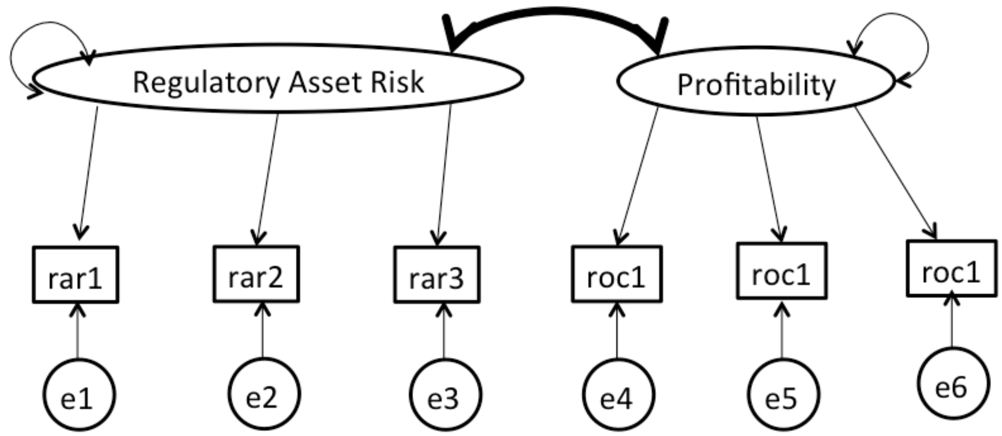

Figure 6: Model5 Path Diagram2

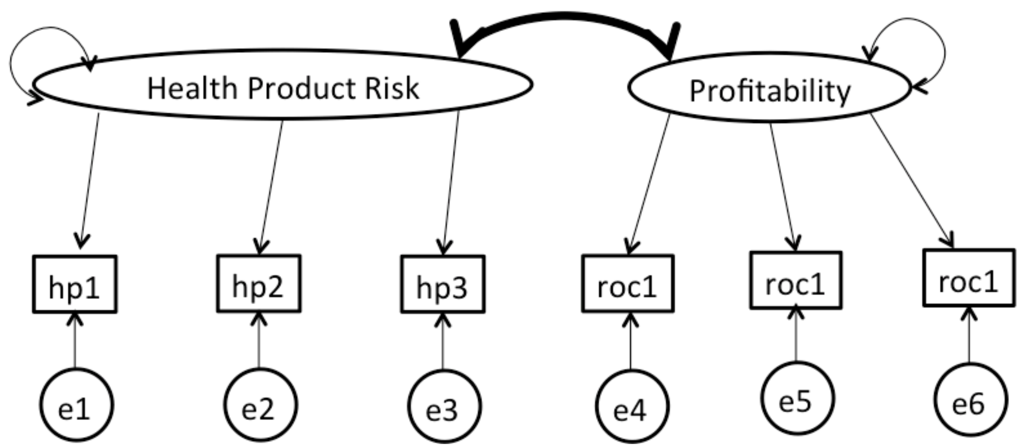

Figure 7: Model5 Path Diagram3

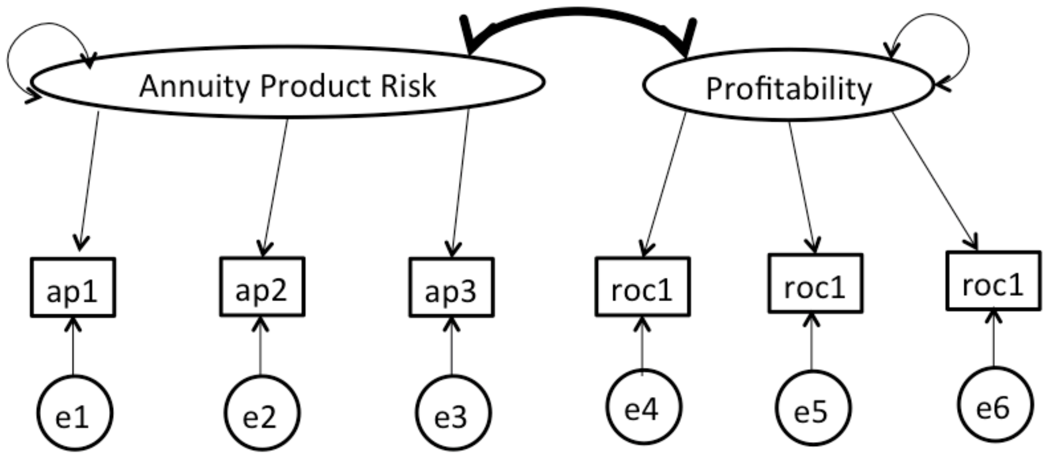

Figure 8: Model5 Path Diagram4

The above four path diagrams share the similar shapes and roles. The motive for doing this is to capture all of the three years' information to show the relation between different latent factors. The results will indicate the correlations between life insurers' profitability and four kinds of risks. This is a compromise between capturing all the information at one time and being parsimonious.

Results

Model 1

	"Product Risk" to "hp"		**"Product Risk" to "ap"**		**"Product Risk" to "roc"**	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
1994	0.2886	5.68	-1.5806	-6.82	0.0252	1.44
1995	0.00172	1.61	0.0242	5.72	-0.0121	-2.51
1996	-0.21	-4.29	1.364	5.44	-0.059	-2.41

Table 11: Model1 Coefficient Results Part1

	"Operation" to "roc"		**"Operation" to "logAtotal"**		**"Operation" to "logincome"**		**"Operation" with "Product risk"**	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
1994	-0.1965	-8.45	1.41	22.17	0.6141	16.23	-0.155	-5.15
1995	0.008	-2.51	1.23	37.56	0.72	23.53	0.1532	8.01
1996	-0.1412	-5.05	1.8736	8.41	0.4679	7.48	0.11	3.69

Table 12: Model1 Results Part2

The fitting in model1 (goodness of fit index = 0.95, 0.98 and 0.94) is acceptable. Judging from the three years results of model1, we can get the following information: first of all, there is not an obvious relation between insurers' product risk and operation ability. And these three years' data does not show that there is much link between product risk and profitability either, since the t-value of "product risk" to "roc" is small, indicating not significant. Secondly, judging from three years' coefficients data, the operation ability seems to have a slight negative effect on the profitability, to be more exactly, the larger life insurers' might have a slight lower return on capital during stable years. So it is probable that small insurers might endure more volatile return on capital during financial crisis, thus the results would likely to be different during other times. The last finding is that life insurers' operation ability loads heavily on "logAtotal" and "logIncome", these two are both size-related measures. This means the operation ability has a positive influence on company size.

Model2

	"Asset Risk" to "oar"		"Asset Risk" to "rar"		"Asset Risk" to "roc"	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
1994	3.06	4.92	-5.6	-38.6	-0.004	-1.1
1995	0.5847	12.81	0.8566	41.69	-0.0491	-1.1611
1996	0.6071	9.49	0.6422	25.27	-0.0927	-2.12

Table 13: Model2 Results Part1

	"Operation" to "roc"		"Operation" to "logAtotal"		"Operation" to "logIncome"		"Asset Risk" with "Operation"	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
1994	-0.22	-9.08	1.26	28.9	0.69	20.33	-0.04	-8.89
1995	-0.0208	-0.5377	0.9486	37.78	0.9234	36.47	0.56	22.04
1996	0.1532	3.6	0.4037	4.77	2.142	5.09	0.066	3.07

Table 14: Model2 Results Part2

The fitting in model2 (goodness of fit index =0.94, 0.97, 0.95) is also acceptable. We can conclude the following deductions from the three years' results: asset risk loads heavily on both opportunity asset risk and regulatory asset risk, but the direction of regulatory asset risk is unclear. So asset risk loads heavily and positively on opportunity asset risk. And there is a slight positive relation between asset risk and operation ability, though the data in 1994 seems not to support that. Thirdly, there is not a significant correlation between asset risk and profitability (represented by return on capital "roc"). However, there is a slight negative relation between operation ability and return on capital. This is in accordance with the results in model1. Finally, similar to model1, logarithm of total assets and logarithm of annual income are loaded heavily and positively.

Model3

	"Solvency" to "oar"		**"Solvency" to "rar"**		**"Solvency" to "hp"**	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
1994	0.00199	0.1174	-0.00509	-0.2997	0.2979	6.0016
1995	0.3021	9.9417	0.414	13.103	0.0243	0.8374
1996	0.8219	16.0163	0.8037	15.8892	0.0920	2.7197

Table 15: Model3 Results Part1

	"Solvency" to "ap"		**"Solvency" to "roc"**		**"Operation" to "roc"**	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
1994	-1.536	-7.2768	0.0271	1.4962	-0.1943	-8.3285
1995	0.5476	16.3617	0.5541	1.9826	-0.6604	-2.4573
1996	-0.0133	-0.3925	-0.0685	-2.0416	0.1364	3.0870

Table 16: Model3 Results Part2

	"Operation" to "logAtotal"		"Operation" to "logIncome"		"Solvency" with "Operation"	
	Coefficient	T-value	Coefficient	T-value	Coefficient	T-value
1994	1.4192	21.44	0.6091	15.86	-0.157	-5.34
1995	1.0686	48.1115	0.8198	32.5761	0.9012	23.86
1996	0.3741	3.93	2.311	4.1397	0.0453	2.72

Table 17: Model3 Results Part3

This model combines the observable variables used in previous models together, it used all of the information, and is more complicated, thus the fit (goodness of fit index = 0.9, 0.91, 0.9)is worse than the previous two, merely passed the "acceptance line". In this model, we combined different risk measures under latent factor "solvency", in order to reflect solvency to some extent. And we can deduce the following from the results: solvency (at least the "solvency" defined in this report) has not much to do with profitability (represented by "roc"). And operation ability mostly has a negative effect on profitability, this is also in accordance with the previous two models. Plus, the relation between operation ability and solvency is unstable, judging from these three years' data.

Model4

	"Operation" to "logAtotal"	"Operation" to "logIncome"
1994	0.9946	0.9054
1995	0.9947	0.9057
1996	0.9947	0.9076
"Operation1" to "Operation2"	0.9948	
"Operation2" to "Operation3"	1.00	

Table 18: Model4 Results

This model analyzes the latent factor "operation ability" longitudinally, and the results proved to be consistent with the outer environment of year 1994 to 1996. Judging from the results, the operation ability in the three years are almost the same.

Model5

Coefficients			
"Opportunity Asset Risk" on "oar1"	0.6732	"Profitability" on "roc1"	0.8246
"Opportunity Asset Risk" on "oar2"	0.9064	"Profitability" on "roc2"	0.4335
"Opportunity Asset Risk" on "oar3"	0.6168	"Profitability" on "roc3"	0.47
"Opportunity Asset Risk" with "Profitability"		-0.01429 (t-value: -0.39)	

Table 19: Model5 Results Part1

Coefficients			
"Regulatory Asset Risk" on "rar1"	0.9041	"Profitability" on "roc1"	0.8236
"Regulatory Asset Risk" on "rar2"	0.9809	"Profitability" on "roc2"	0.4330
"Regulatory Asset Risk" on "rar3"	0.9275	"Profitability" on "roc3"	0.4699
"Regulatory Asset Risk" with "Profitability"		-0.0427 (t-7value: -1.25)	

Table 20: Model5 Results Part2

Coefficients			
“Health Product Risk” on “hp1”	0.8339	“Profitability” on “roc1”	0.82
“Health Product Risk” on “hp2”	0.9910	“Profitability” on “roc2”	0.4343
“Health Product Risk” on “hp3”	0.9611	“Profitability” on “roc3”	0.4715
“Health Product Risk” with “Profitability”		-0.0278 (t-7value: -0.82)	

Table 21: Model5 Results Part3

Coefficients			
“Annuity Product Risk” on “ap1”	0.879	“Profitability” on “roc1”	0.827
“Annuity Product Risk” on “ap2”	0.9996	“Profitability” on “roc2”	0.437
“Annuity Product Risk” on “ap3”	0.9541	“Profitability” on “roc3”	0.472
“Annuity Product Risk” with “Profitability”		-0.109(t-7value: -3.34)	

Table 22: Model5 Results Part4

This model consists of four path diagrams. It uses three years information to decide the relation between profitability and other latent factors. The results showed that asset risk does not have much to do with profitability, whatever regulatory asset risk or opportunity asset risk. And health insurance product risk does not correlate with profitability either. While the strange thing we found out in this model is that annuity product risk has a slightly negative correlation with profitability. The truth is that annuity product is least risky and should provide the most stable cash flows for life insurers. This is probably because during the financially stable years, the products with highest risks tend to have lower risks because of less default rate, thus they are more profitable than the low risk products. It could also because the relation between product risk and profitability is complicated and bringing them out to analyze separately might not tell the whole story. It could also because we need more data from other years to prove us the closer results.

Summary and Discussions

This is an confirmatory study on the different competences interactions in the field of life insurers. The report used structural equation modeling, for this method is not only a kind of an exploratory factor analysis method, but it can also bring latent factors into the model. Latent factor is a perfect fit when doing research on abstract concepts, in this case, the different "competences" or "abilities" of life insurers. We built several models, in order to get a rather complete view of this issue during the years 1994, 1995 and 1996. We did this also because of model parsimony concerns. We analyzed the data within each year and longitudinally.

Through all of these models, we found that operation ability indeed has a positive influence on the size and income of life insurers. And the loadings on logarithm of total assets and logarithm of annual income are high. And we found out that the operation ability of life insurers do not differ much between these three years, that is to say, the operation runs rather smoothly.

We also discover that almost all the models show that operation ability has a slight negative effect on the return on capital during these years. While the effect of solvency, asset risk and product risk on return on capital is not significant and unclear. Meanwhile, there is not much evidence showing that there is any correlation between operation ability and solvency ability.

There are some limitations in this study. First of all, we could also extend these models into other years to see if there is any difference, such as financial crisis times. This could give us a broader view on the subject. Secondly, the fittings of the models are not that ideal. Though the fittings in 1995 are relatively better, it can still improve. This is probably mostly due to the slight difference between the characteristics of structural equation modeling and the characteristics of financial indicators of life insurers. In other words, structural equation modeling is originally designed for psychological and social science survey or test studies, their data are more subjective and tend to cluster together due to similar traits or testing techniques. However, in the realm of insurance industry, the data is far less subjective and we have already done our best to find the homogeneous traits across similar observable variables. This could possibly be improved by increasing sample groups (add more years data) and dig deeper into the related theories of life insurers industry.

Appendix: SAS code

```
data tmp1.y93_08;
set tmp1.y93_08;
oar = log(popparisk);
rar = log(pregarisk);
roc = retoncap;
hp = prodhrisk * 100;
ap = prodarisk * 100;
/*negincome = sign(income) * log (1 + abs(income));*/
/*if  roc > 3 or roc < -2 then  roc = .;*/
proc calis data = tmp1.y93_08  (where=(year=1994))
covariance residual modification maxiter =130000 maxfunc = 130000;
var  hp ap roc logAtotal logincome;
lineqs
hp = b1 F_pro +   e1,
ap = b2 F_pro + e2,
roc = a2 F_ope + b3 F_pro + e3,
logAtotal = a1 F_ope + e4,
logincome = a3 F_ope + e5;
STD
F_pro F_ope = 1.0 1.0,
e1 e2 e3 e4 e5 = e_var1 e_var2 e_var3 e_var4 e_var5;
cov
F_pro F_ope = phi;
run;
proc calis data = tmp1.y93_08  (where=(year=1995))
covariance residual modification maxiter =20000 maxfunc = 20000;
var  hp ap roc logAtotal logincome;
lineqs
hp = b1 F_pro +   e1,
ap = b2 F_pro + e2,
roc = a2 F_ope + b3 F_pro + e3,
logAtotal = a1 F_ope + e4,
logincome = a3 F_ope + e5;
STD
F_pro F_ope = 1.0 1.0,
e1 e2 e3 e4 e5 = e_var1 e_var2 e_var3 e_var4 e_var5;
cov
F_pro F_ope = phi;
run;
proc calis data = tmp1.y93_08  (where=(year=1996))
covariance residual modification maxiter =200000 maxfunc = 200000;
var  hp ap roc logAtotal logincome;
lineqs
hp = b1 F_pro +   e1,
ap = b2 F_pro + e2,
roc = a2 F_ope + b3 F_pro + e3,
logAtotal = a1 F_ope + e4,
logincome = a3 F_ope + e5;
STD
F_pro F_ope = 1.0 1.0,
```

```
e1 e2 e3 e4 e5 = e_var1 e_var2 e_var3 e_var4 e_var5;
cov
F_pro F_ope = phi;
run;
proc calis data = tmp1.y93_08  (where=(year=1994))
covariance residual modification maxiter = 200000 maxfunc = 200000;
var roc oar rar logAtotal logincome;
lineqs
oar = a1 F_sol + e1,
rar = a2 F_sol + e2,
roc = a3 F_sol + b1 F_ope + e3,
logAtotal = b2 F_ope + e4,
logincome = b3 F_ope + e5;
STD
F_sol F_ope = 1.0 1.0,
e1 e2 e3 e4 e5 = e_var1 e_var2 e_var3 e_var4 e_var5;
cov
e1 e2 = a12,
F_sol F_ope = phi;
run;
proc calis data = tmp1.y93_08  (where=(year=1995))
covariance residual modification maxiter = 200000;
var roc oar rar logAtotal logIncome;
lineqs
oar = a1 F_sol + e1,
rar = a2 F_sol + e2,
roc = a3 F_sol + b1 F_ope + e3,
logAtotal = b2 F_ope + e4,
logIncome = b3 F_ope + e5;
STD
F_sol F_ope = 1.0 1.0,
e1 e2 e3 e4 e5 = e_var1 e_var2 e_var3 e_var4 e_var5;
cov
e1 e2 = a12,
F_sol F_ope = phi;
run;
proc calis data = tmp1.y93_08  (where=(year=1996))
covariance residual modification maxiter = 20000 maxfunc = 20000;
var roc oar rar logAtotal logIncome;
lineqs
oar = a1 F_sol + e1,
rar = a2 F_sol + e2,
roc = a3 F_sol + b1 F_ope + e3,
logAtotal = b2 F_ope + e4,
logIncome = b3 F_ope + e5;
STD
F_sol F_ope = 1.0 1.0,
e1 e2 e3 e4 e5 = e_var1 e_var2 e_var3 e_var4 e_var5;
cov
e1 e2 = a12,
F_sol F_ope = phi;
run;
proc calis data =  tmp1.y93_08  (where=(year=1994))
```

```
covariance residual modification maxiter = 200000 maxfunc = 200000;
var roc oar rar logAtotal logincome hp ap;
lineqs
hp = a1 F_sol + e1,
ap = a2 F_sol + e2,
rar = a3 F_sol + e3,
oar = a4 F_sol + e4,
logAtotal = b1 F_ope + e5,
logincome = b2 F_ope + e6,
roc = a5 F_sol + b3 F_ope + e7;
STD
F_sol F_ope = 1.0 1.0,
e1 e2 e3 e4 e5 e6 e7 = e_var1 e_var2 e_var3 e_var4 e_var5 e_var6 e_var7;
cov
F_sol F_ope = phi;
run;
proc calis data =  tmp1.y93_08  (where=(year=1995))
covariance residual modification maxiter = 20000 maxfunc = 20000;
var roc oar rar logAtotal negincome hp ap;
lineqs
hp = a1 F_sol + e1,
ap = a2 F_sol + e2,
rar = a3 F_sol + e3,
oar = a4 F_sol + e4,
logAtotal = b1 F_ope + e5,
negincome = b2 F_ope + e6,
roc = a5 F_sol + b3 F_ope + e7;
STD
F_sol F_ope = 1.0 1.0,
e1 e2 e3 e4 e5 e6 e7 = e_var1 e_var2 e_var3 e_var4 e_var5 e_var6 e_var7;
cov
F_sol F_ope = phi;
run;
proc calis data =  tmp1.y93_08  (where=(year=1996))
covariance residual modification maxiter = 200000;
var roc oar rar logAtotal negincome hp ap;
lineqs
hp = a1 F_sol + e1,
ap = a2 F_sol + e2,
rar = a3 F_sol + e3,
oar = a4 F_sol + e4,
logAtotal = b1 F_ope + e5,
negincome = b2 F_ope + e6,
roc = a5 F_sol + b3 F_ope + e7;
STD
F_sol F_ope = 1.0 1.0,
e1 e2 e3 e4 e5 e6 e7 = e_var1 e_var2 e_var3 e_var4 e_var5 e_var6 e_var7;
cov
F_sol F_ope = phi;
run;
```

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